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Fingerprint Segmentation Approach for Human Identification

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Abstract: Biometrics are essential in facility access control where human characteristics are used for person identification. Fingerprint is a basic identity for verification. Fingerprint segmentation is an open problem in biometrics, hence it is the first process towards the utilization of fingerprints for human recognition because each individual has a unique and permanent fingerprint sample. Considering this uniqueness, Fingerprint-based human verification is used in several applications for a an era. A fingerprint image is considered as a pattern which composed of two regions, foreground and background. The foreground contains the significant information utilized in the fingerprint identification systems. However, the background is usually noisy, distorted and unstable region that plays an important role in the extraction of false minutiae in the fingerprint system. In order to avoid this, we use fingerprint segmentation to isolate foreground/background fingerprint composites. Threshold, Entropy and Type-2 fuzzy-logic based fingerprint segmentation are presented and compared in this work. furthermore a demonstration of Fingerprint-based human verification approach that employee the presented segmentation techniques is presented and evaluated using ROC curve to prove the validity and reliability of proposed methodology.

Keywords: Fingerprint, Segmentation, Verification, Threshold, Entropy, Type-2 Fuzzy-Logic, Receiver Operating Curve, Wilcoxon Test.

1 Introduction

Fingerprint-based systems of human recognition is the most ancient recognition system among all the biometrics techniques. each individual has a unique and unchangeable fingerprint. For example iris and fingerprints of the twins are even different. Based on this uniqueness and distinctness, fingerprint identification is used in many applications for a long period.A fingerprint can be defined as a pattern composed of ridges and valleys on the surface of the finger [1,2]. It can be changeable only by some environmental and job-related factors such as cuts or injuries on the finger. These factors make the system unsuitable in some degree. Generally, the accuracy of the fingerprint recognition is sufficient in many applications especially in Forensics. To allow great identification systems for a large number of identities, the systems require having a multiple fingerprint from the same person to give additional information [1,3]. Fingerprint is totally established at nearly seven months of fetus development and it is unique and unchangeable during individual's hurts or unwilling injuries. A fingerprint is composed of a series of ridges and valleys on the surface of the finger itself. In the image point of view, ridges are really the dark part in the image except the existence of different kind of noise, meanwhile valleys are the bright part. Evenly, ridges and valleys go in parallel but sometimes they bifurcate or terminate. Bifurcation exists when the ridge suddenly split into two ridges and termination exist, both bifurcation and termination are a representation of some important minutiae points. Minutiae mean small details that can determine important local features in the fingerprint minutiae types that are the following:

–Termination.
–Bifurcation.
–Lake.
–Independent Ridge.
–Point or Island.

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–Spur.
–crossover.

Automatic fingerprint identification or verification systems rely on minutiae matching [2,3]. The most important step in minutiae-based matching is to extract reliably the minutiae points from the input image. This extraction depends on the efficiency of the detection of ridges and valleys in the fingerprint segmentation step. Therefore an accurate segmentation of fingerprint images produces an effective result in automatic fingerprint recognition system. Fingerprint image consists of two parts, foreground part that is the essential area for extracting minutiae points, and background part that is the noisy area. Segmentation of the fingerprint image is to decide which part from the image is associated with the foreground and which part is associated with the background. Due to the nature of fingerprint image and the presence of noise, the decision for separating these two regions is critical. The fingerprint image can be affected by many conditions that perform the segmentation to be a challenging task. The first problem is the presence of dust and grease in the scanner's sensor. The second one is the presence of some traces from previous image acquisition [4,5]. The last one is the contrast of fingerprint that can be influenced by the dryness or the wetness of the finger. For dry finger, fingerprint contrast is low and the contrast is high for wet finger.

2 Related Work

Generally, image segmentation methods are classified into two categories, discontinuity and similarity of intensity value. In the discontinuity-based categories, segmentation can be defined as edge-based segmentation that subdivides an image based on abrupt changes in the intensity. In the similarity-based categories, the segmentation is related to partitioning an image into regions according to their similarity. The similarity is a measure that is defined in advance depending on the fundamental problem in the image. This measure can be a specific intensity level, mean value, variance value, and so on. Point, line and edge detection are examples of discontinuity methods. Also, threshold, Otsu, splitting and merging and region growing are examples of similarity-based methods. The combination between different methods can give an improvement in segmentation performance. Many identification algorithms were presented to solve almost the same problems. The background was not separable from the foreground. In [3], authors presents a novel approach for fingerprint verification enhancement via combining a set of pre-processing filter-banks in what is so called ISM_1 and ISM_2. Chunxiao et al. [6] propose a hybrid method based on blockwise taxonomy to distinguish the foreground from the background and pixelwise classifier to operate pixels accurately. Marques and Thome [7] partitioned the image into different sub-blocks, and then extracted a feature vector relying on its descriptors of Fourier transform. Each one of these vectors is passed to an artificial neural network to classify it. In [8] authors presented a novel online unsupervised ridges detection method based on fuss taxonomy techniques. In [9] authors presented a novel algorithm that firstly applies the method of gradient projection, then adopts gradient coherence and finally carry out morphological operation to exact the foreground region. Zhu et al. [10] proposed a technique for systematically deducting a fingerprint ridge orientation and segmenting fingerprint via evaluating the pureness of ridge orientation using artificial neural network. The artificial neural network as a classifier [11] is used to learn the correctness of the estimated orientation by gradient-based method, meanwhile it could be used as an automatic foregroung/background separation method [12] via perfroming efficient edge detection [13]. Helfroush and Pour [4] used a combination of three variance mean and ridge orientation features and also employs the median filter as a post-processing step. Akram et al [14] presented a modified gradient based method to extract region of interest. This method compute the local gradient values for fingerprint images which detect sharp change in the gray-level value of background. In [15], Bazen and Gerez proposed also an algorithm that uses three-pixel features, being the coherence, which is the mean and the variance. An optimal linear classifier is trained for the taxonomy per pixel, while morphology is applied as post processing. Yin et al. [16] show two steps for fingerprint clustering to exclude the remaining ridge region. The non-ridge regions and distorted low quality ridge regions are deleted as background in the initial step, and then the foreground constructed by the initial step is more analyzed so as to remove the remaining ridge region.

The main contribution of this work is to present some fingerprint segmentation techniques. Segmentation methods are applied to isolate the most important components of the fingerprint which is called the foreground. Also presents some pre-processing techniques for fingerprint enhancement. Presented methodologies are quite demonstrated mathematically and applicably. The methods for fingerprint segmentation are chosen to be quit distinct and comparable. Threshold is the basic segmentation method presented, then maximum entropy concept ends with type-2 fuzzy-logic technique. The histogram equalization is demonstrated as a well-known filtering technique for fingerprint image enhancement.

The rest of the paper is organized as follows: in section 3 the fingerprint segmentation techniques are presented each in a subsection. In section 4.1 the filtering technique that's so called histogram equalization is demonstrated. In section 5 the used database in experiment is presented, meanwhile the main results, discussion and work conclusion are presented in sections 6,7.

3 Fingerprint Segmentation Methodology

3.1 Threshold method

In threshold methods, a threshold T can separate foreground/ background. This threshold can be selected according to mainly the intensity of the image histogram. Histogram of an image shows the gray-level values versus the number of pixels at that defined T value. Any pixel with gray-level $F(x,y) > T$ is assigned as a foreground; otherwise the rest of pixels is assigned as background

$$\begin{cases} G(x,y) = 255 & \text{IF} \quad f(x,y) > T \\ G(x,y) = 0 & \text{IF} \quad f(x,y) \leq T \end{cases} \tag{1}$$

For fingerprint images, the histogram displays the contrast of the image and the statistical distribution of the gray level. Because of the nature of fingerprint images, the meant algorithm can't apply a normal threshold method.

3.2 Maximum entropy method

Considering $H(I)$ as a normalized histogram [17] of image I, we have

$$\sum_{i=0}^{i_{max}} h(i) = 1. \tag{2}$$

Typically i takes integer values from 0 to 255. Entropy of black pixels

$$H_B(t) = -\sum_{i=0}^{t} \frac{h(i)}{\sum_{j=0}^{t} h(j)} \log \frac{h(i)}{\sum_{j=0}^{t} h(j)}. \tag{3}$$

Entropy of white pixels:

$$H_W(t) = -\sum_{i=t+1}^{i_{max}} \frac{h(i)}{\sum_{j=t+1}^{i_{max}} h(j)} \log \frac{h(i)}{\sum_{j=t+1}^{i_{max}} h(j)}. \tag{4}$$

Optimal threshold can be chosen by maximizing the entropy of black/ white fingerprint image pixels:

$$T = \arg_{t=0 \dots i_{max}} \max(H_B(t) + H_W(t)). \tag{5}$$

In case if we aim to find optimal n thresholds, the Equation 5 would be generalized from one threshold to n thresholds as follows:

$$T_1, \dots, T_n = \arg \max_{t_1 < \dots < t_n} H(-1,t) + H(t_1,t_2) + H(t_n, i_{max}) \tag{6}$$

Where:

$$H(t_k, t_{k+1}) = -\sum_{i=t_k+1}^{t_{k+1}} \frac{h(i)}{\sum_{j=t_k+1}^{t_{k+1}}} \log \frac{h(i)}{\sum_{j=t_k+1}^{t_{k+1}}} \tag{7}$$

3.3 Type-2 Fuzzy-Logic Method

The original fuzzy logic (FL), or named Type-1 FL, cannot handle (that is, model and minimize the effects of) uncertainties seems paradoxical because the term fuzzy has the connotation of uncertainty. We believes that Type-1 FL captures the uncertainties and vagueness, But, in reality, Type-1 FL handles only the vagueness, not uncertainties, applying a precise membership functions (MFs). When the Type-1 MFs have been selected, all uncertainty vanish because Type-1 MFs are totally precise. Type-2 FL, on the other hand, handles uncertainties hidden in the information/data as well as vagueness by sampling these using Type-2 MFs. All set-theoretic operations, for example union, intersection, and complement for Type-1 fuzzy sets, can be done in the same way for the Type-2 fuzzy sets. Procedures for doing this have been worked out and are especially simple for Type-2 fuzzy sets [18]. A classical set A can be defined as a group of member elements that could either belong to or not belongs to set A. Whereas as according to fuzzy set, which is a generalization of classical set, an element member can partially belongs to a set A. Whereas A can be defined as:

$$A = \{(x, u_A(x)) | x \in X\}, 0 \leq u_A(x) \leq 1 \tag{8}$$

where $u_A(x)$ is called the membership function, which calculates the nearness of x to A. The following membership function can be derived for n level segmentation or clustering.

$$u_1(k) = \begin{cases} 1 & k \leq a_1 \\ \frac{k-c_1}{a_1-c_1} & a_1 \leq k \leq c_1 \\ 0 & k > c_1 \\ \vdots & \end{cases} \tag{9}$$

In practice we can use the following formula for the fingerprint segmentation where the entropy of ordinary fuzzy set A, is:

$$H(A) = (\sum S_n(\mu_A(x)))/n.\ln 2 \tag{10}$$

Where
$S_n(\mu_A(x)) = -\mu_A(x) ln(\mu_A(x)) - (1 - \mu_A(x)) ln(\mu_A(x))$.
Therefore we can define a function $\gamma(A)$ where:
$\gamma_{\min} = H_{\min} = 0$ for μ=0 or 1.
$\gamma_{\max} = H_{\max} = 1$ for μ=0.5. Therefore, γ and H are monotonic functions and increase in the interval $[0, 0.5]$, meanwhile they decrease in $[0.5, 1]$ with a maximum of one at $\mu = 0.5$. So it is possible to use one or the other formula to define the uncertainty degree.

4 Fingrprint-based Human Verification

the main challenges against constructing a robust verification biometric system mainly using the human fingerprints are low quality, noise, distortion and rotation. Histogram Equalization (Hist-Eq) technique in the backbone of preprocessing stage to overcome most biometric images drawbacks. After applying the Hist-Eq algorithm, we used the well-known Local Binary Pattern (LBP) algorithm for feature extraction process.The fingerprint segmentation techniques are applied separately to separate the fingerprint foreground/ background.

4.1 Histogram Equalization

Hist-Eq technique is a common approach for adjusting image intensities in order to improve the low-quality image contrast. Hist-Eq increase the contrast of the image by lowering the number of gray levels in that image [19]. In the equalization process, the neighbouring gray levels with light probabilistic density are fused into one gray level, while the gap between two neighbourhood gray-levels with heavy probabilistic density is increased. Let f be a given image represented as a $[m_r * n_c]$ matrix of integer pixel intensities ranging from 0 to 255, L is the number of available intensity values, often 256. Let P represent the normalized histogram of v with a bin for each possible intensity. Consequently:

$$p_n = \frac{\textit{Number of pixels with intensity n}}{\textit{Total number of pixels}}, \quad n = 0, 1, \ldots, L-1 \tag{11}$$

The histogram equalized image is defined by:

$$g_{i,j} = \lfloor (L-1) \sum_{n=0}^{f_{i,j}} p_n \rfloor \tag{12}$$

where the floor $\lfloor . \rfloor$ rounds down to the nearest integer.

4.2 Local Binary Pattern

LBP is such an efficient method for texture operator and feature extraction. It is based on computing a value of a local region around each pixel of the image by thresholding the neighbourhood of each pixel then extracting the outcome as a dual binary value [20]. In addition, a uniform pattern is applied for decreasing the depth of the feature vector and doing a simple rotation-invariant descriptor. When the LBP labels are calculated, uniform patterns are applied as a separated label for each uniform pattern and all the non-uniform patterns are labelled altogether. At first LBP operator is restricted to a small 3×3 neighbourhood with limit features.

Figure 1[1] shows the extended LBP operator which has two parameters (P, R). P is several neighbours sampling

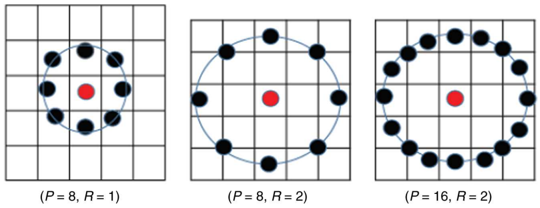

Fig. 1: A different sizes of LBP neighbourhoods.

points on a circle of radius of R. So, when using (8, R) neighbourhood, there are a total of 256 patterns, which yield in 59 different labels, where:

$$H_i = \sum_{x,y} I\{f_l(x,y) = i\}, i = 0, \ldots, n-1, \tag{13}$$

When the image patches whose histograms are to be compared have different sizes, the histograms must be normalized to get a coherent description:

$$N_i = \frac{H_i}{\sum_{j=0}^{n-1} H_j}. \tag{14}$$

5 Experimental Settings

The Fingerprint Verification Competition 2006(FVC 2006) of 4^{th} edition databases for fingerprint verification [21]. In FVC 2006, unique mark impressions are assembled with four sensor devices about 150 fingers wide and 12 samples/person in depth (1800 fingerprint images). The acquired fingerprint images in FVC2006 were collected with a low-quality. The proposed algorithm pseudo steps are described in algorithm 1.

Algorithm 1 Describes the pseudo steps of proposed Fingerprint-based human verification framework.

Require: A Fingerprint Database.
Ensure: An Efficient Fingerprint-based Human Verification System.

Training Phase:

1. Using methodology described in sections: 3.1,3.2,3.3 evaluate Foreground/ Background separation process.
2. Generate User Template Database using technologies in Section: 4.

Test Phase:

1. Using Technologies in Section:4 Produce the Test Database.
2. Compute the evaluation metrics such as ROC and Wilcoxon test.

[1] Figure source: M Sultana et al; Local binary pattern variants-based adaptive texture features analysis for posed and non-posed facial expression recognition.

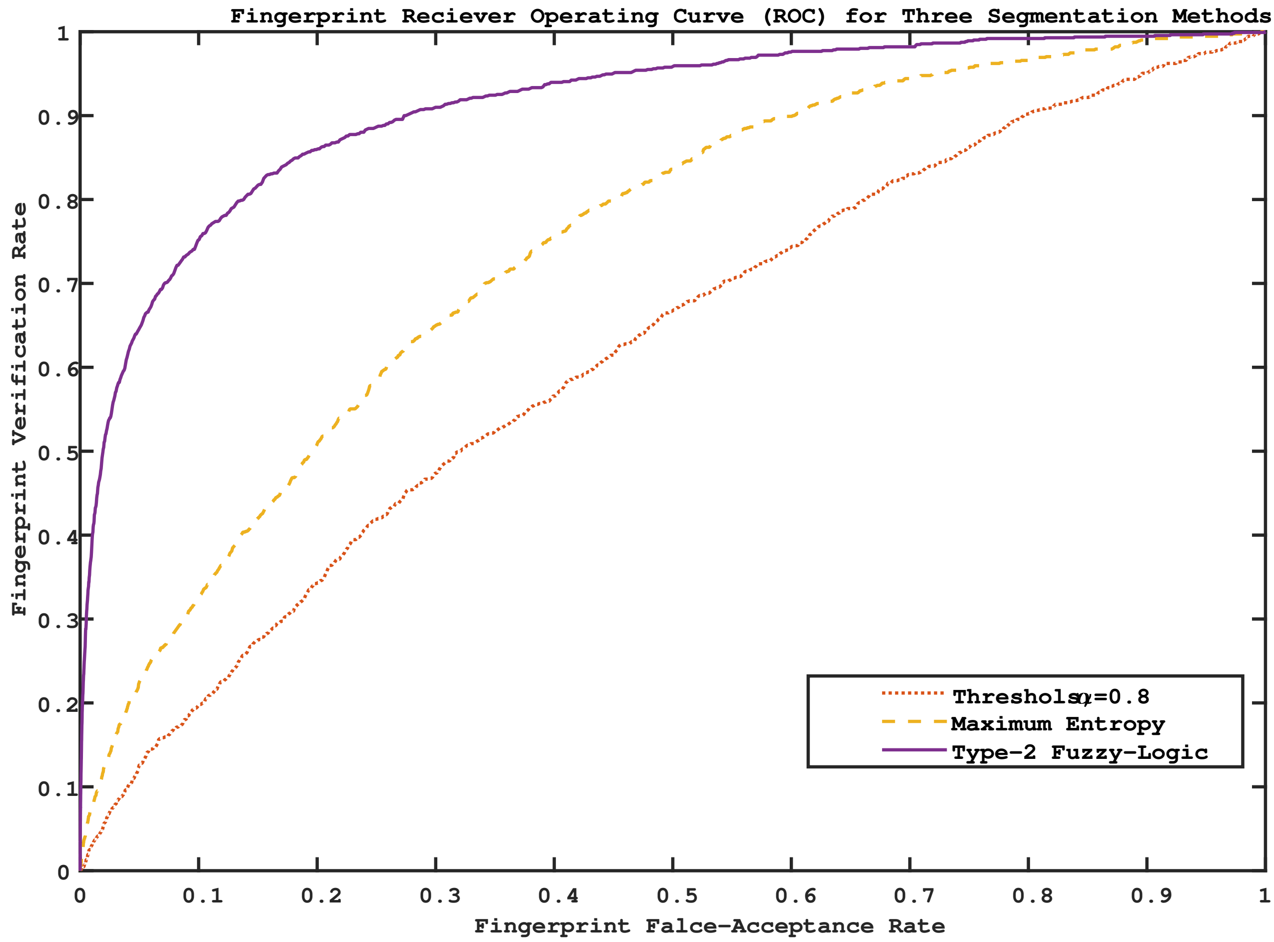

Fig. 2: ROC curves for fingerprint verification, a comparison between the effect of fingerprint segmentation techniques.

6 Experimental Results

The proposed method is tested using different quality images from the fourth edition benchmark FVC database (FVC2006–DB2A). To assess the fingerprint identification system performance, we use Receiver Operating Characteristic curve (ROC curve). Then, the obtained results are analysed and evaluated.

6.1 Wilcoxon Signed-rank Test (W)

The **W**-test is a non-parametric statistical hypothesis test used when comparing two related samples, matched samples, or repeated measurements on a single sample to assess whether their population mean ranks differ [22]. We evaluate the fingerprint Template/ Test matching results for each Foreground/ Background segmentation method separately as a processing tool to enhance the fingerprint image clarity via separating the fingerprint foreground/background. Then each segmented fingerprint is enrolled in the recognition stage. The final scored accuracy in the verification stage is evaluated via the **W**-test to investigate the scored accuracy significance.

Table 1: An evaluation of fingerprint segmentation methods performance by **W**-test

α	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Theshold	T2FL 21	T2FL 24	T2FL 21	T2FL 22	T2FL 22	T2FL 21	T2FL 21	Theshold 21	T2FL 21
Entropy	Entropy 22	T2FL 21	T2FL 20	T2FL 23	T2FL 21	T2FL 21	T2FL 22	Entropy 23	T2FL 22
T2FL	T2FL 21	T2FL 24	T2FL 21	T2FL 22	T2FL 22	T2FL 21	T2FL 21	T2FL 21	T2FL 21

In Table 1, the evaluation of T2FL against Threshold, Entropy using the **W**-test for FVC2006 dataset is presented. The first row represents threshold α values as $\alpha = \{0.1, 0.2, \cdots, 0.9\}$. The comparison of Threshold with T2FL is given in the second row which shows that T2FL is better than Threshold at all α values except when $\alpha = 0.8$ according to the numbers (**W**=21) given in this row. These numbers represent the **W**-test values for the winner method in each comparison at each α value. In the third row, the comparison of Entropy with T2FL is given and the **W**-test values shown that Entropy is winner only when $\alpha = (0.1, 0.8)$ according to the numbers (**W**$=22, 23$) given in this row.

6.2 Receiver Operating Characteristics Curve

ROC curve is a graphical plot that illustrates the performance analysis and evaluation of biometric system as its discrimination threshold is varied [23]. The curve is created by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. In figure 2, the evaluation of ROC curves is shown for threshold, maximum entropy and type-2 fuzzy-logic. It is found that the best method identification rate from the T2FL and the performance improvement is obtained. Thus, the results clearly explain that high identification rate could overcome fingerprint image distortion, noise and false minutiae drawback effects.

7 Discussion and Conclusion

Unimodal fingerprint verification systems proven to be improved and overridden using either multimodal biometric systems or matching score combination rules. In this paper, we proposed a unimodal approach rely on the utilization of three fingerprint segmentation methods and single enhancement approach. Those technologies were applied in the preprocessing stage to overcome the main drawbacks in fingerprint acquisition systems. Then, feature extraction is done using the famous LBP algorithm. Presented methods were applied and evaluated by means of verification accuracy, computational complexity and run-time mean and standard deviation over whole experimental runs. The performance of the demonstrated Fingerprint-based human verification using Hist-Eq in preprocessing stage and T2FL for fingerprint Foreground/ Background segmentation is proven to outperform other considered segmentation techniques.

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